I. Description of the Proposed Training Program

I.1. Overview

We request support for an interdisciplinary pre-doctoral training program at Carnegie Mellon University that will prepare a new generation of researchers who will be (a) grounded in cutting-edge theories and methodologies in cognitive and developmental psychology, statistics, human-computer interaction and instructional technology; (b) familiar with many of the fundamental problems facing education in America: and (c) committed to applying their skills and knowledge to solving those problems. Our plan is to build upon our already existing interdisciplinary programs in Psychology, Human-Computer Interaction, Statistics, and several other departments, and to expand and integrate the existing opportunities for rigorous training in educational research that are currently distributed across our campus. We will refer to this new training program as the Interdisciplinary Educational Research Program (IERP).

1.2. The Problem

The challenges of scientific research in education and the pressing need for well-trained educational researchers are succinctly stated in the Request for Applications (RFA) and widely discussed in the educational research literature (cf. Berliner, 2002: Carver & Klahr, 2001: Feuer, Towne, & Shavelson, 2002; Hoffer et.al., 2003; Lagemann, 2000; Miller, 1999; NRC 2002, Viadero, 2004). As the RFA points out, the existing institutional structures and human capital flows in educational research fail to produce a sufficient number of adequately trained researchers. Moreover, most of the new PhDs graduating from rigorous disciplinary programs (e.g., in Computer Science, or Statistics, or Psychology) with the skills necessary to conduct rigorous educational research are unaware of the exciting challenges and opportunities in this area, and therefore disinclined to apply their training to real-world educational problems. That we need to train a new breed of scientists who view education as their primary research area is well established. The question is: "How do we do it?"

1.3. A Proposed Solution

In our view, one answer lies in substantially expanding and formally institutionalizing the kind of pre-doctoral training in educational research that currently exists only in piecemeal form at Carnegie Mellon University. In this section, we provide a few examples of this training and research, and note that although it is of very high quality, it does not form a coherent, well-integrated program for doctoral students interested in educational research. Then we describe the way in which our proposed IERP would create a powerful and well-defined program focused on pre-doctoral training in educational science.

1.3.1 Current Research at CMU in Education Science.

In every scientific domain, a strong graduate program can only exist within the context of an excellent program of faculty research. At CMU, educationally focused research is being conducted by faculty in several departments. Some of this work is focused on problems in education outside CMU, from K-12, and at the university level. Other work is focused on college level instruction, and uses CMU and other universities as the research site. Below, we briefly indicate a sample of these research programs in order to provide a sense of the breadth and quality of these research programs.

• Cognitive Tutors developed at CMU have provided the basis for much of the cutting edge research on how students learn in a variety of domains. The tutors for high-school mathematics are now in some 1700 schools, used by over 150,000 students per year (Corbett, Koedinger, & Hadley, 2001; Koedinger, Anderson, Hadley, & Mark, 1997). A number of current and prior

graduate students and post docs have been involved in intelligent tutoring work that includes middle school mathematics as well as high school. Cognitive Tutors are also expanding to college level courses (Statistics, Genetics, Economics, Logic, Causal Reasoning). Both Anderson and Koedinger's research on cognitive tutors is supported, in part, by IES grants.

- Lovett's research on how college students learn introductory statistics has led to the development of a cognitive tutor for data analysis called StatTutor (Lovett. 2001: Meyer & Lovett. 2002). StatTutor's design is based on learning theory and results and now offers a platform for further elaborating that body of theory (work funded by NSF). In addition. StatTutor is part of a broader CMU effort to develop a fully on-line statistics course that integrates educational research into its design (work funded by Hewlett Foundation).
- David Klahr and Junlei Li are engaged in a project that will develop, implement and assess cognitive-grounded lesson planning methods to improve science achievement in middle school children in urban schools. The project involves close cooperation with classroom teachers, and a research-teacher design experiment approach. (This work is funded by IES).
- Siegler's research on the development of mathematical and scientific reasoning with children in kindergarten through eighth grade employs trial-by-trial assessments of individual children's problem solving strategies and microgenetic methods to generate in-depth analyses of how children learn to solve arithmetic. estimation, proportionality, and a host of other educationally-important problems. (This work is funded by IES).
- Project LISTEN's Reading Tutor (Mostow, et al., 2003a) is used daily on hundreds of computers by children in elementary schools in Pittsburgh and North Carolina, as well as in field studies by ESL researchers at University of British Columbia, University of Toronto, and DePaul University. Dissertations relating to this project include Aist (2001) and Pane (2002).
- Scheines' online course on Causal and Statistical Reasoning (CSR), which is part of the Open Learning Initiative (www.cmu.edu/oli/), has now been offered to over 2.700 students at over 30 colleges and universities nationwide, including large research universities in California and small liberal arts colleges in rural Kansas. Scheines, Koedinger, and Lovett are core participants in OLI, which is developing over a dozen online college courses and studying how to optimize the educational effectiveness of such courses. Over the next five years, OLI courses will have a "test bed" of dozens of institutions of higher education across the nation. Parts of Scheines' CSR course are now a permanent part of at least three different undergraduate courses at Carnegie Mellon, as well as a required course at the University of Pittsburgh. A particular benefit of these four offerings is the range of students covered. At Pitt, we are teaching lower level math phobic undergraduates who are trying to avoid calculus, and at CMU we are using the material in at least one upper level course designed for technically gifted students.

1.3.2. Existing Pre-doctoral Training at CMU Relevant to Education Science.

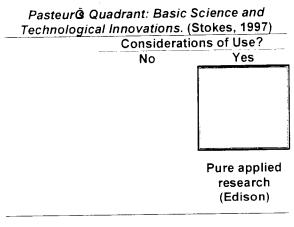
Corresponding to these extensive and diverse research activities addressing educational problems is a set of graduate students who have been part of the various research teams. These students comprise a kind of "invisible" pre-doctoral training program in education science at CMU. Their training, taking place in several of our strongest disciplinary programs, is currently only partially integrated. Nevertheless, for at least the past 20 years, CMU's world-class departments of Psychology, Statistics, Philosophy, and Computer Science have produced a stream of PhDs with a primary interest in problems and topics that are central to educational research. A list of these graduates, and the topic of their research and/or current positions, is provided in Tables A1 and A2 in the Appendix.

For example, recent contributions to the education literature from Statistics PhDs include the following: Junker & Gitelman, 2002; Patz & Junker, 1999; Patz, Junker, Johnson, & Mariano, 2002; Mariano & Junker, 2004; Erosheva, 2004; McCaffrey, Lockwood, Koretz, Louis & Hamilton, 2003, 2004; Lockwood, Doran, & McCaffrey, 2003. Drs. Lockwood, Haviland and Mariano are all employed as Statisticians at the RAND corporation with portfolios that include substantial education research. Dr. Johnson is an academic statistician in the Department of Statistics and Computer Information Systems, Zicklin School of Business, Baruch College, CUNY. Dr. Patz became Senior Research Scientist and head of the research group at CTB/McGraw-Hill. Dr. Erosheva is an academic statistician with the Center for Statistics and the Social Sciences (CSSS) at the University of Washington: the CSSS's research portfolio includes social aspects of educational research. In Computer Science, two recent examples include Gregory Aist (Aist, 2001) and John Pane (2002), both of whom have worked on project LISTENs reading tutor. Dr. Aist is now on the research faculty at Rochester University and Dr. Pane is at RAND.

1.3.3 Previous Obstacles to a Full-fledged Graduate Program in Education Science

These individual cases, while exemplifying the kind of pre-doctoral training and career path needed to advance educational research, do not comprise an institutionally integrated, programmatically coherent, and academically visible training program in educational research. They represent an assortment of piece-meal – albeit very successful -- initiatives by individual students and their advisors. At present, Carnegie Mellon University lacks systemic support and infrastructure for training doctoral candidates in educational research. The key reasons for this gap and rationales for change are summarized below.

• In very strong discipline-oriented departments, such as those at CMU, there is often a perceived status differential between basic and applied work, in which basic, disciplinary research is deemed more important, higher quality, and more difficult than applied work. Indeed, it is interesting to note that several of the most influential cognitive psychologists who have contributed to educational research made the move from "lab to field" only after they were very well



established (and tenured!) in their basic discipline (e.g., Ann Brown, Robbie Case, John Bransford, among others.) This status problem has been widely lamented by those within the profession of educational research (cf. Berliner, 2002; Labaree, 2003). However, in recent years, this perspective has been challenged, both here and in the broader research community. As Stokes (1997) points out in his influential book, there is a "spreading realization of how multiple and complex and unequally paced are the pathways from scientific to technological advance: of how often technology is the inspiration of science rather than the other way around: and of how many improvements in technology do not wait upon science at all." The IERP training program proposed here would be firmly rooted in "Pasteur's Quadrant" (see Table), where the research agenda is inspired by use and application, but grounded in the quest for fundamental understanding within each discipline.

• The lack of a visible cohort of educationally-minded faculties and peers within individual departments makes inefficient the creation of specially-focused courses and activities addressing educational research. Lacking formal academic program, projects, and departmental encouragement, educationally-motivated students question the appropriateness and status of "educational" research in world-class departments devoted to basic research. Most of our students adopt the values of their disciplinary culture and perceive their careers to be advanced more by basic than by applied work. Consequently, the majority of PhD's from our departments have traditionally pursued basic research during graduate studies and sought faculty positions within their disciplines (i.e., in Departments of Psychology, or Computer Science, etc.), rather than in institutions dedicated to educational research (i.e., School of Education, educational think-tanks). Our IERP proposes to aggregate these students across departments into a clearly identifiable and highly visible interdisciplinary training program. This integration will create a "critical mass" necessary to justify special graduate curriculum focused on the education sciences. We are confident in the potential of this integration, based on the knowledge that there have already been a number of exceptions to the general tendency towards basic research at Carnegie Mellon University (see Appendix for the listing of graduates who have pursued challenging career paths in which applied educational research is their primary activity). This small but substantial contingent of researchers demonstrates the potential for IERP to institutionalize the drive and momentum for disciplinary researchers to focus their efforts on educational research.

I.3.4 Overcoming Obstacles: a new Interdisciplinary Educational Research Training Program at Carnegie Mellon University

The proposed training grant would enable us to create a clearly identified, and programmatically organized pre-doctoral training program in educational research that would substantially reduce all of these barriers. More specifically, the pre-doctoral training program proposed here would: (a) capitalize on all of the existing, but widely dispersed, strengths of our current educational research efforts; (b) significantly increase the number of students engaged in educational research across the university; (c) correspondingly increase the opportunities for faculty to engage in collaborative teaching and research activities related to educational problems; (d) foster a strong cross-departmental cohort of pre-doctoral students with a set of common courses, seminars, interests, and career paths; (e) provide a well-defined identity, vision, and common core of training and experience for students aiming to become educational researchers; (f) consequently, provide a high-visibility graduate training opportunity that would attract excellent students into careers in educational research.

I.4. Three Themes in the Proposed program

I.4.1. Theme A: Educational Research Requires a Continual *Bi-directional* Flow of Ideas and Challenges from Basic Laboratory Studies to Real-world Instructional Applications.

As noted in the earlier allusion to Pasteur's Quadrant, a common view of the relation between disciplinary knowledge and educational practice is that there is a unidirectional flow in which "basic" research has precedence, then it gets compromised by the realities of applied work, and then "engineered" into a useful product. Graduate training in the IERP will be based on a different perspective. An underlying theme in our training will be that there is recurring cycle from lab to field back to new fundamental questions about thinking and learning. For example, when Toth, Klahr & Chen (2000) transformed their method for teaching middle school students the rudiments of experimental design from a laboratory script to a classroom lesson plan, they encountered several important new questions that they then explored back in the psychology lab.

These issues included questions about how children understood error and variability (Masnick & Klahr, 2003), whether physical or virtual presentations of materials had an impact on learning (Triona and Klahr, 2003), and how well children can generate and interpret external notations (Triona and Klahr, in press). Students in our training program would be presented with both the skills and the opportunities that will enable them to cycle their research activities back and forth across this "basic-applied-basic" interface.

I.4.2 Theme B: Knowledge Assessment at Multiple Grain Sizes (Temporal and Cognitive) Knowledge assessment might be viewed as CMU's greatest contribution to the cognitive sciences. Starting 40 years ago with the unprecedented precision with which Newell & Simon analyzed verbal protocols in order to advance understanding of human problem solving, and continuing through a variety of powerful knowledge assessment methods, such as eye movement recording, chronometric analysis, fMRI, microgenetic analysis, rule analysis, and computational modeling. CMU researchers have developed and applied powerful methodologies that inform us about how people acquire, represent, remember, and utilize knowledge. Much of this work came out of research programs in the Departments of Psychology and Computer Science, but the contributions of researchers in other CMU departments have also been substantial. For example, overlapping research programs in Philosophy. Human Computer Interaction, and Statistics -- all partners in the proposed IERP -- have produced modern techniques for "data mining" that are being applied to the massive real-time student log files generated by intelligent tutoring systems. The importance of such new assessment procedures is the central message in the recent NRC volume, which also argues for the importance of linking cognitive science and psychometrics in knowledge assessment (NRC 2001)¹. These cutting edge knowledge assessment techniques provide another theme in our training program.

I.4.3 Theme C: Leveraging Educational Technology for Educational Research.

Rigorous educational research requires collecting and analyzing data. Collecting data via traditional field studies is necessary, but expensive and difficult, and analyzing it intelligently takes substantial statistical training. Teaching PhD students how to use educational technology for efficient data collection and analysis will pay huge educational research dividends in the 21st century, during which the use of educational technology will almost certainly rise substantially. By "analysis" we mean going beyond traditional methods for significance testing, to the use of state-of-the-art data-mining techniques for generating causal hypotheses about which sorts of student behaviors and teaching strategies lead to better learning outcomes (e.g., Spirtes, Glymour, Scheines, 2000: Scheines, Leinhardt, Smith, Cho, 2003). Although Randomized Field Trials (RFTs) are a powerful method for making causal inferences (NRC, 2004), they are but one tool in the toolbox of scientific research in education. Further, non-RFT methods are useful for other than causal questions. For example, clustering student behavior patterns in problem solving tasks leads to hypothesis generation for further investigation or causal evaluation. Thus, an important component of our training program will be to see that our students master a rich variety of statistical methods appropriate to educational research contexts, and that they understand the strengths and limitations of each.

Carnegie Mellon is uniquely situated to provide interdisciplinary training to PhD students in both data collection with educational technology and in the analysis of such data with state-of-

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¹ Several of the IERP faculty contributed to this volume, including David Klahr, who was on the NRC committee. Ken Koedinger, who was an invited workshop participant, and Brian Junker, who wrote a commissioned paper that provided the basis for Chapter 4 of the Committee report.

the-art data mining. The Pittsburgh Advanced Cognitive Tutor Center which has designed and deployed cognitive tutors for algebra, geometry, and several programming languages, has used logs of student behaviors as a central feature of their iterative design process, and they have leveraged these data into some of the best educational research in the field today. (http://www-2.cs.cmu.edu/~pact/index.html) For example, the Open Learning Initiative (OLI) at Carnegie Mellon (http://www.cmu.edu/oli/) has recently incorporated logging technology that can record student activity in online courses and in virtual problem solving environments. It has already been used to log more than 3 million interactions between students and the educational technology engaging them. These data have already proven useful in understanding what makes online instruction effective (e.g., frequent comprehension checks are crucial). OLI is now combining forces with the cognitive tutor group to standardize logging and develop simple tools for analyzing log data.

Project Listen (http://www-2.cs.cmu.edu/~listen/) has pioneered the use of speech recognition technology in teaching elementary school students how to read (Mostow & Aist. 1997. Mostow et al., 1994). Stringent evaluations have demonstrated pre- to post-test gains compared to various control conditions (Mostow et al., 2002; Mostow et al., 2003a: Mostow et al., 2004, in press). In addition, automated experiments embedded in the Reading Tutor randomize tutorial interventions (Aist, 2001: Mostow, to appear), and capture data at multiple grain sizes on student interventions (e.g., offers of help to the student) and outcomes (e.g., successful word identification). Project LISTEN has mined such data to assess student proficiencies (Mostow et al., to appear), test tutorial interventions (Mostow et al., 2003b: Mostow et al., 2004), monitor implementation fidelity and analyze motivational variables (Mostow et al., 2003c). For example, the aggregated database for the 2003-2004 school year already includes over 50.000 sessions, 60.000 story readings, 1.500.000 sentences, 500.000 requests for help on words, and 10 million words heard. Data from previous years have been used by graduate students in Language Technologies. Computer-Assisted Language Learning, and Knowledge Discovery in Databases.

As to analyzing the data collected by educational technology, the Center for Automated Learning and Discovery (CALD) (http://www.cald.cs.cmu.edu/) combines statisticians. computer scientists, and faculty from many other fields in an interdisciplinary center devoted to developing techniques, both theoretical and practical, for generating interesting hypotheses about domains as disparate as FMRI images, web-based job descriptions, and educational data. CALD has faculty who are leaders in using computers to search for interesting causal hypotheses from observational data.² as well as faculty who are leaders in mining educational data.³

1.5 Basic IERP Curriculum

Pre-doctoral training in all of the participating departments uses an "augmented research apprenticeship" model, in which students are immediately engaged in research, and in which a small core of fundamental courses are required, and augmented according to each student's background, strengths, needs, and goals. The IERP curriculum would enrich this model by adding a few central core courses, while still adhering to each participating department's basic approach to graduate training. The design for our curriculum is based in part on the existing doctoral programs in Psychology, Statistics, and Computer Science, and in part on the highly successful PhD training program used in a similarly interdisciplinary program in the Center for the Neural Basis of Cognition (CNBC). Although CNBC has a different research agenda than

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² Richard Scheines, Peter Spirtes, and Larry Wasserman, for example,

³ Joe Beck and Jack Mostow from Project Listen, for example.

ours, its administrative and programmatic issues are similar to those we face. (And we have a highly experienced administrative and support staff that is familiar with these types of interdepartmental doctoral training programs.) Thus we can draw on more than a decade of experience in the CNBC in crafting our own program.

The IERP curriculum has five components: research, coursework, teaching, seminar participation, and the Integrative Interdisciplinary Activity (IIA, see Section I.5.3). The goal of the program is the training of researchers who can apply the basic techniques of cognitive and developmental psychology, statistics, and human-computer interaction, among others, to the study of educational problems. We aim to produce scientists who can not only do research on education, but also teach at the university level.

I.5.1 Overview of Curriculum

Here we emphasize only those features of the IERP that distinguish it from the normal PhD program in the participating departments. The IERP program requires four core courses, which constitute 1 to 4 additional courses beyond the student's doctoral program's regular training requirements, depending on their admitting department. Students are encouraged to augment their training with additional electives based on their needs. All trainees will be expected to meet the teaching requirements in their home departments. (Usually amounting to serving as a TA for a total of 2 or 3 courses during the 5 year training program.)

<u>Years 1 and 2</u>. Students will participate in the following activities: (a) Departmental and core courses, including a graduate course in research methods and ethics. (b) Research conducted under the direction of a faculty advisor. (c) Other academic courses as required by the home department. (d) At least 2 of the IERP-related courses described in section I.5.2. (e) The IERP colloquium series. (f) IERP student-run activities (e.g., journal clubs, seminar series, brown bags).

<u>Year 3</u>. For most students, this will be the year in which, trainees will participate in the two integrated interdisciplinary Activities described below (Section I.5.3).

<u>Years 4 & 5</u>. The major objective of the fourth and subsequent years is to complete the doctoral dissertation. This is normally accomplished by the end of the fifth year depending on the home department requirements. By the end of the Fall Term of the fourth year, students develop their dissertation proposals and establish their dissertation committees. The dissertation committee will include at least one member of the IERP program committee.

I.5.1.1 Research.

Each student is expected to participate in original research throughout the five years of graduate study. Students are expected to select an Advisory Committee soon after arrival. Each Advisory Committee will have at least one member from outside the student's home department. representing another department that is part of the IERP. The Advisory Committee assists the student in the selection of a research topic, guides the progress of the research, and continually evaluates the outcomes of that research. In the Spring of both the first and second years, each student prepares a research paper in the form of a journal article and gives a formal presentation of that project to their home department, as well as the others in the IERP. Students are encouraged to complete additional research in these years as well.

In the summer between the second and third year, each student prepares a review paper assessing the state of knowledge concerning a basic issue within the student's broad area of study. It is our intent that these papers be of sufficient quality that they might be submitted to a journal such as *Psychological Bulletin*, *Educational Researcher*, AERJ. *Journal of Educational and*

Behavioral Statistics. A dissertation proposal is prepared during the fourth year. In the fifth year, students are expected to produce and defend their dissertation.

Each year, trainees report on their research activities in a one-hour talk given in the Spring. These talks are required of first and second year graduate students. Advanced students typically replace these in-house talks with warm-up talks for presentations at scientific meetings. These one-hour research presentations provide a valuable opportunity for interaction among students, postdocs, and faculty.

I.5.1.2 Seminar Participation

Students are expected to participate in a wide variety of departmental seminars and colloquia. These colloquia provide a rich opportunity both for predoctoral and postdoctoral students to meet with various researchers, to learn about important concepts in their area, and hear about other research approaches and results. In addition to these discipline-oriented invited colloquia, we will organize a special educationally oriented set of talks, probably two each semester, that would be required for all of our students.

Another important intellectual opportunity is the annual CMU Symposium on Cognition. These three-day long symposia are organized around a central theme and result in a published volume that constitutes one of the most respected series in cognitive psychology. One of the recent symposia focused on the link between cognition and instruction (Carver & Klahr, 2001) The symposia provide an opportunity for outstanding researchers to describe their work and meet with faculty and graduate students. Colloquium series are also sponsored by Computer Science. Statistics, the Tepper Graduate School of Business, and the Heinz School of Urban and Policy Administration, among others.

1.5.2 Description of IERP-related Courses

In this section we provide excerpts from the syllabi of several of courses that would be available to IERP trainees. At present, because of the relatively small number of interested students in any one year, most of these courses are offered only infrequently, and are often cross-listed both as graduate and advanced undergraduate courses in order to have viable class sizes. However, under the estimated size of the IERP cohort (approximately 20 in steady state; see Section I.6.2), we could offer these courses on a regular basis, keep them limited to graduate training, and correspondingly increase their rigor.

Scientific Research in Education (Klahr) Perhaps the most influential piece of education legislation passed in recent years is the 2002 "No Child Left Behind Act" (NCLB). Two of the most widely-known consequences of the law are (a) its emphasis on testing and assessment and (b) NCLB's repeated emphasis on *scientifically based education research* (cf. NRC, 2002). But what does "scientifically based education research" mean? Scientists, historians, philosophers of science, and politicians have debated this question for more than 100 years. Does it mean the sort of studies that cognitive and developmental psychologists do when they are interested in how students think about math or science? Does it mean massive national randomized field trials on the effect of class size or teacher certification? Does it have to include the kind of emphasis on underlying mechanisms that we (in Pittsburgh!) are so interested in discovering? Can it include non-experimental, qualitative, case studies and field demonstrations? Does it require statistical significance, or large effect sizes, or both? Must it include new technologies or traditional teacher-student interactions? What constitutes a treatment or an independent variable: a lesson, a tutorial intervention, a unit, a course, a curriculum? What is the appropriate "unit size": individual students, classrooms, teachers, schools, or school district? This course provides an

introduction to these questions, and to some of the perspectives and methods that have been used to address them. We will read and critically evaluate two types of papers: (a) those focusing on some of the broad policy issues, as well as some of the highly contentious debates in the literature about the nature of educational research: (b) those that appear in the psychology and education journals -- relating to research on how people learn science and mathematics. These two types of papers will be interleaved throughout the course so that we get a sense of the interaction between basic research in education and "hot" policy issues.

Applications of Perceptual and Cognitive Psychology (Klatzky) The course focuses on applications that are sufficiently advanced so as to have made an impact outside of the research field per se. That impact can take the form of a product, a change in practice, or a legal statute. Another criterion is that the application be grounded in theoretical primitives at the level of cognitive process and/or biological model. This criterion excludes, for example, pure measurement research, as in ergonomics. Examples of education-related applications that meet these criteria are cognitive tutors based on models of cognitive processing, phonologically based reading programs, latent semantic analysis applications to writing assessment, and analogy-based instruction. The approach of the course will be to consider a group of applications in detail, while building a general understanding of what it means to move research into the applied setting. The questions to be considered include: What makes a body of theoretically based research applicable? What is the pathway from laboratory to practice? What are the barriers? Economic, legal, entrenched belief, or practice?

Research Methods in Psychological and Educational Research. (Siegler.) This course covers both randomized and non-randomized field study designs, as well as a variety of knowledge assessment techniques, such as rule assessment, eye movement analyses, chronometric methods, and protocol analysis. Many of the examples involve educational contexts. This course provides a grounding in basic principles of experimental design, as well as a wide variety of specific methods useful for studying learning and instruction

How Children Learn Mathematics. (Siegler) This graduate seminar would focus on children's acquisition of arithmetic concepts and procedures, based on the most recent research findings. Topics would include children's learning of counting: arithmetic: estimation: fractions, ratios, and proportions: and algebra. The course begins with major theories of mathematics learning — Piagetian, neo-Piagetian (Case), Behaviorist (Gagne), neo-nativist (Wynn, Gelman), constructivist (Steffe), and information processing (Siegler, Klahr, Anderson) — and then reviews major empirical findings and emerging issues in the field.

Educational Technology: Data Collection and Analysis (Scheines and Beck). This course will cover how to collect data from educational technology applications, and then how to analyze it especially for the purpose of generating hypotheses about the causes of learning outcomes. Students engage in a wide variety of activities while learning: they read, they write, they ask for help, they solve problems, they talk to their peers, they navigate through a website, etc. The deep challenge in information technology research is to figure out what, of the information we could record, is ultimately useful in helping the student learn either by providing feedback to the student directly, or indirectly via educational researchers, content authors, teachers, administrators, software developers, cognitive science researchers, and even the instructional software itself. The first half of this course will cover successful methods for logging useful data from educational applications. The second half of the course will examine techniques for generating interesting educational hypotheses - especially causal hypotheses, from large, usually correlational datasets. We will discuss Causal Bayes Networks, techniques for learning them

from data, clustering techniques, exploratory factor analysis and other latent variable discovery algorithms, as well as several other machine learning and data mining techniques. In each case, our focus will be on the particular challenges and opportunities offered by datasets taken from educational contexts, especially ones that involve technology. The course will involve at least one substantial project involving the collection of data from a live educational context. Educational Goals. Instruction, and Assessment (Carver) The aim of this course is to teach students how to develop educational goals based on a detailed task analysis of the knowledge. skills, and dispositions required for mastery of a particular aspect of a domain. Goals for early childhood, elementary, middle school, and high school will be discussed and related to the state and national standards. A comprehensive understanding of student achievement will be developed. The importance of matching the instructional program and its assessment to goals will be discussed and demonstrated. Assessment that focuses on covering the full range of specified goals will be studied along with diverse approaches for valid assessment. Other topics include making instructional material choices, funding, classroom management, ethics, and relation to system-level policies. Assignments will emphasize linking goals - instruction assessment. A term project will consist of an in-depth study of one central unit in a discipline or grade level.

1.5.3 Year 3 courses: Integrative Interdisciplinary Activities.

The training grant is predicated on 5 years of training, in departments where the nominal length of PhD training is 4 years. The extra year is required for two reasons: (a) the additional courses -- described above -- that will augment the typical course requirements within each of the participating departments will reduce the pace of research that students can accomplish without these extra required courses. (b) two integrative interdisciplinary activities (IIA) that are unique to the IERP. In this section we describe the nature of, and rationale for, these two activities.

1.5.3.1. The Interdisciplinary Educational Research Project The purpose of this project is to institutionally integrate educational research opportunities within each department into interdisciplinary collaborative projects. All IERP students, from whatever department they come, will be required to complete this interdisciplinary project before their fourth year in the program. Under the supervision and guidance of faculty from three of the core departments (e.g., Psychology, Human Computer Interaction Institute, and Statistics), predoctoral students will be expected to form project teams consisting of other IERP students from different disciplines. These teams will execute projects that integrate research from multiple disciplines. Such projects will not only utilize suitable methodologies and theoretical frameworks from each discipline, but will also strive to innovate in the area of interdisciplinary integration. Students will explore how the methods and perspectives of each discipline can adapt, complement, and enhance each other. For example, how could a promising finding in basic cognitive research be applied to instruction, using effective HCI implementation, and assessed via multiple data points integrated by robust statistical analysis? The projects will be evaluated by faculties and peers on the basis of their disciplinary merit and interdisciplinary innovation.

1.5.3.2 Field-based Research Project (FRP) The aim of the field-based research project is to enable field-and-use inspired research pilot studies and concepts prior to dissertation phase of graduate studies. During this "professional immersion" year of the predoctoral academic track, as graduate students begin to formulate and solidify their dissertation concept, it is critical for them to experience and appreciate the real-world constraints encountered in educational research. The aim of the FRP is to help students to develop project management, organizational, and research skills necessary to conduct research in field settings. The FRP will require students to formulate

and conduct short-term research projects that are situated in the field of practice (e.g., K-12 classrooms, college classrooms, etc.). Students will have to go through the full cycle of field research in educational settings: planning the research protocol, recruiting participants and facilitators at several levels (e.g., teachers, classrooms, students), submitting IRB proposals, and immerse their research in the field of actual practice. The FRP would be closely supervised by faculty members most experienced in field research. Students would be encouraged and supported in "stretching" their "home" methodology for these projects. For example, a psychology student in basic cognitive research might choose to adopt an engineering design approach to study the effect of a research-based intervention on 1st graders' reading, or an HCI student with expertise in intelligent tutor design might undertake an ethnographic study of middle-school students' everyday interaction with computers, or a statistics student might offer to help to interpret the massive standardized test scores for urban school administrators and teachers to identify the potentially causal links between students' reading, writing, IQ, and overall academic achievement. In addition to providing students in this track with the necessary field experience, improving their abilities to understand practitioners' needs and to communicate directly with teachers and children, this course also hopes to serve as a launch pad for fieldinspired dissertation projects in the students' fourth and fifth year.

The two integrative IERP activities described above are designed to complement and facilitate each other. The experience of interdisciplinary collaboration would allow students to learn from each other the diverse methods and techniques that could be applied in the educational setting. The experience of field study would provide the fertile soil from which the seed for applied research could blossom. Students will be responsible for providing a written report at the end of each semester that summarizes their specific FRP experiences and discusses how they lead directly to new questions and research on education. Ideally, this experience will be influential in the trainee's choice of a dissertation topic.

I.6 Recruiting

The training program will be advertised through several means: (a) A dedicated website describing the program (linked to the regular graduate web site of each participating department): (b) A professionally-designed brochure sent to targeted departments across the country. These departments will include all of the types of departments represented in this proposal (i.e., Psychology, HCI, Statistics, etc.), as well as the top tier schools of education. This brochure would be directed to the department heads and directors of undergraduate programs in those departments. (c) Targeted individuals will be identified from several sources, including those currently holding grants from IES, faculty in schools of education with a focus on the domain foci of this proposal, researchers holding educationally oriented grants from ONR, NSF, and NIMH, especially IERI grants, as well as related private foundations such as Spencer. Russell Sage, and A. W. Mellon, among others. (d) The regular distribution channels used by each of the participating departments, each of which will add a brief description of this special program to their regular graduate recruiting materials, with a pointer to our IERP web site. (e) Advertisements in the appropriate venues from professional society journals in each of the participating disciplines. (f) We also will advertise the program through the annual minority students' recruitment conference (see Section I.7 for more detail on minority recruiting).

1.6.1 Selection

Candidates for the IERP must first be admitted into their respective departments via the normal review process. Each department will include an option on their admissions forms for students to indicate that they are interested in the IERP. All of the faculty advisors on the training grant will

review the complete set of applications in their respective departments order to identify the top candidates, based upon letters of reference, undergraduate record, including research experience (e.g., as Research Assistants, interns, etc.), GRE's, background in educational contexts (e.g., as teachers), commitment to educational research, and evidence of potential productivity. Each department, during its normal graduate admissions process will identify students whom they deem appropriate for support from the IERP training grant and forward that slate to the IERP Program Committee, who will make the final selection of IERP candidates.

Each of the participating graduate programs is highly selective: in Psychology, approximately 100 students apply each year, and 9 or 10 are admitted; the Human Computer Interaction Institute similarly receives about 100 applications and admits about 10 students; Statistics receives about 175 applications and accepts about 20, and Philosophy gets 60 applications and admits 2 PhD students; the Department of Computer Science receives over 800 applications and accepts about 20; the Center for Automated Learning and Discovery (see Section I.4.3) receives about 125 applications and admits 5 or 6 new doctoral students each year. The average time to completion in Psychology is between 4 and 5 years for programs in cognitive, social and developmental psychology, with about a year extra for candidates in the CNBC program. (Summary data for the Department of Psychology is listed in the Section A.2 of the Appendix.)

1.6.2 Growth and Size of Program

The estimated number and distribution of trainees across the participating departments over the 5-year period of requested support for is shown here. For the 2004-05 AY, enrollment is based on our estimates

	2004-05	2005-06	2006-07	2007-08	2008-09
Psych Stat	4	7	9	9	9
Stat	1	3	4	4	4
HCII	2	3	4	4	4
Other	0	2	3	3	3
Total	7	15	20	20	20

of *current* PhD students in each department whose interests and planned career paths would qualify them for IERP support. The following years are based on estimates of *new* students entering, starting in the Fall of 2005, and estimated completion dates of those entering in 2004 and thereafter. Note that there is nearly a three-fold increase from the size of our current "hidden and distributed" IERP cohort and the program that we will be able to support with the requested funds. (See Budget Notes for a more detailed analysis of the flow of trainees through the program.)

1.7 Minority Outreach and Recruiting

At present we have few minority students in any of our graduate programs. Our central focus on cognitive psychology, neuroscience, statistics, and human computer interaction has made it particularly difficult to recruit minority graduate students, who, according to the statistics that we extract from APS and APA are typically more interested in social psychology, child development, and educational policy issues. We believe that with the integrated and highly visible focus on applied educational problems that we will be able to attract many more highly qualified minority students into our program. We are optimistic about this because we will have substantial institutional support and guidance in our endeavors.

At the University level. Carnegie Mellon has established a commission on under-represented minorities. The commission has gathered systematic data on the percentage of different minority groups among faculty, students, and staff and has recommended new policies and practices for creating and maintaining a culturally and racially diverse environment. The university has developed a number of programs designed to improve the status of under-represented minorities. These include the Carnegie Mellon Action Project, Heinz School programs for graduate and

professional training of minorities, programs designed to stimulate minority graduate recruitment, and outreach activities aimed at increasing the university's role in addressing the needs of Pittsburgh's minority communities. These latter activities include a Community Literacy Center and extensive involvement by the President with the Pittsburgh Regional Economic Revitalization Initiative.

Richard Scheines, one of the core IERP faculty and member of its Program Committee (see Section II.2), is also the Director of the Undergraduate program in Human Computer Interaction at CMU. He will be proactive in recruiting minority undergraduates into that program, and in identifying those who should be encouraged to apply to this graduate training program.

The Department of Psychology collaborates with the MUSE (Minority Undergraduate Students of Excellence) program of the American Psychological Association, which each year identifies minority students with interests in graduate study in Psychology. The Head of the department has also attended special sessions devoted to minority recruitment at the annual meeting of the Council of Graduate Departments of Psychology. Our department and the university as a whole embrace the goal of a diverse environment. We will continue to make use of the MUSE program and we will also contact chairs of departments through the Council of Graduate Departments of Psychology to solicit minority applications. Despite our efforts at contact and recruitment, no MUSE student has applied thus far. To increase applications from underrepresented minority groups, we will collaborate with the Directors of our NIMH Training Grant, in pursuing several related efforts: (a) Following the model of the National Consortium on Violence Research, we will work with the Morehouse Research Institute and the six independent colleges of the Atlanta University Center to involve advanced undergraduates in our research programs with the goal of interesting them in graduate school. (b) We will collaborate with a program to bring African American undergraduates to Pittsburgh for summer research experiences, which is currently being organized through a member of the University of Pittsburgh's Board of Trustees, Frederick S. Humphries, who is President of Florida A&M University. (c) We will include a special communication regarding our interest in underrepresented minority candidates in our advertisements in professional journals in the disciplines participating in the IERP. (d) We also include a statement regarding our interest in underrepresented minority recruitment in the graduate brochure. (e) We maintain contact with underrepresented minority group research centers, such as the Center for Minority Mental Health Research of NIMH for help in recruiting underrepresented minority candidates. (f) We will broaden our contact with individual colleagues to locate trainees from these particular underrepresented minority groups. (g) We will work with current trainees to devise additional ways of recruiting underrepresented minority candidates.

Earlier this year the President of CMU met with many departments around the University to discuss ways of increasing minority recruitment of graduate students. It was agreed that Indira Nair. Vice Provost for Education at Carnegie Mellon, would establish a program that brought undergraduate students to CMU for a summer term in their Junior year.

II. Institutional Commitment, Management, and Program Evaluation

Carnegie Mellon University is committed to supporting this program at all administrative levels. Appendix A includes letters of support from CMU's President, Jared Cohon, from the Dean of the College of Humanities and Social Sciences (John Lehoczky), from the Head of the Department of Psychology (Michael Scheier), from the Head of the Human Computer Interaction Institute (Dan Siewiorek).

II.1 Program Director

The IERP Program Director will be Professor David Klahr. In addition to his research contributions in cognitive development and early science education. Dr. Klahr is an experienced research and education manager, and is familiar with many of the leading issues surrounding the "hardening" of the Learning Sciences. He was Head of CMU's Department of Psychology for 10 years, is a former director of the Psychology Graduate program, and has recently served on two NRC committees studying educational issues: the Committee on Educational and Psychological Foundations of Assessment (NRC, 2001), and the Committee on Research in Education. In recent years, Dr. Klahr has been invited to present his views on the linkage between basic research in cognitive development and early science instruction at two major NSF grant holders meetings, at recent annual meetings of the American Psychological Association and the American Psychological Society, and at the Secretary of Education's Science Summit.

II.2 Management and Evaluation

The IERP Program committee will, in coordination with the participating departments, select students for the IERP and will meet on a regular basis to review course offerings, semi-annual reviews of student progress, coordination of field activities, budget allocations, and other aspects of the IERP. The committee will consist of representative faculty from the primary participating departments. At the outset, this will include Sharon Carver, Teaching Professor and Director of the Carnegie Mellon Children's School: Brian Junker, Professor, Statistics Department: David Klahr, Professor of Psychology (Committee Chair): Ken Koedinger, Associate Professor, Human Computer Interaction Institute and Psychology Department; Marsha Lovett, Assistant Professor of Psychology; Brian MacWhinney. Professor of Psychology; Jack Mostow, Principal Research Scientist, Robotics Institute, Richard Scheines, Professor, Philosophy, Center for Automated Learning and Discovery and Human-Computer Interaction Inst; Robert Siegler, Professor of Psychology.

Program Committee will (a) refine and monitor the common educational core for the IERP. Students will then work out a full curriculum with their advisors, who will ensure that the requirements of the admitting department are also met): (b) monitor the set of IERP related courses that our students will be taking: (c) ensure that the students' educational plans will enable them to complete the requirements of the home department, as well as their IERP related courses and research within the 5 year period of their doctoral support. (d) Ensure that students remain in good standing both in their home departments, as determined by their graduate evaluation procedures, and in the IERP program, as determined by periodic assessments of course performance, research progress, and participation in other aspects of the IERP.

As noted earlier, we envision not a single sequence of required courses for all graduate students in the SLC, but rather a set of courses from which students will choose, depending on their backgrounds and goals. Decisions about when to offer these courses, and which students should take them will be determined jointly by the students' advisors and the IERP Program Committee.

III. Participating Faculty and Their Educationally Oriented Research Programs

Here we list the research interests of the faculty who are likely to participate in the training of IERP pre-doctoral graduate students. While this listing describes the most likely initial set of participants, we plan to be flexible and opportunistic in our decisions about which students to support under this training grant, as the interests of both faculty and students develop over time, with respect to the relevance of their research to education science.

John Anderson. Professor of Psychology and Computer Science. The goal of my research is to understand how people organize knowledge that they acquire from their diverse experiences to produce intelligent behavior. Our theory is called ACT-R (Anderson & Lebiere, 1998) and takes the form of a computer simulation which is capable of performing and learning from the same tasks that subjects in our laboratories work at. Our research has two major branches. First, in the laboratory we are looking at how people learn and solve problems in very well-defined situations. Here we are interested in things like how strategies for problem-solving evolve, how people discover things about a new domain, how they deal with the working memory load imposed by the tasks, and how they get faster at accessing information relevant to task performance. The other branch of our research involves a much broader focus. We have taken on modeling the cognitive competences that are taught in the domains of mathematics, computer programming, and cognitive psychology. Much of the motivation for this research is to be able to tap into real situations where people learn and solve problems and understand the implications of these domains for the cognitive architecture. We have built larger-grain ACT-R simulations that are capable of solving problems in these domains and have developed computer-based instruction around these cognitive models. Many of these computer-based instructional systems have the cognitive models as a component and attempt to understand student behavior by actually simulating what the student is doing in real time. These are called cognitive tutors and are currently being used to help teach courses in schools around the country. Much of this research is part of a major effort to produce a significant improvement in American mathematics education.

Joseph Beck, System Scientist, Project LISTEN. What can we learn from observing students interacting with educational software? Can such observations cause us to revise our theories of how students learn? Can we use such observations to create a theory of how children learn? My research focuses on educational data mining, specifically determining what information, from a large stream of data describing student interactions with computer software, is useful and how it can be used. Ideally, educational software would be constructed from a well-validated theory of how students learn and how material should be presented. Unfortunately, some domains suffer from a lack of such theories (or from having too many, contradictory, theories). Furthermore, many theories are designed with human instructors in mind and may not be optimal for use with computers. Finally, even user interfaces that are designed according to theory and that should be understandable to users need to be tested. For educational systems, in addition to interface concerns, it is possible that user testing will reveal that students are not learning as predicted by the pedagogical theory being used. The results of user testing can reveal problems that either cause the original theory to be revised or serve as the catalyst for the construction of a theory of how users interact with this particular software. Using fine-grained interactions between the student and computer to construct specialized theories has been the thrust of my research. Recently I have been working with a database of student-tutor interactions recorded by Project LISTEN's Reading Tutor, a computer tutor for reading that listens to children read aloud. This database contains over 750,000 utterances by students collected from over 20,000 student sessions with the Reading Tutor. These data were collected as a byproduct of a controlled experimental trial, but were not themselves part of a controlled study. Determining what to do with data that have not been collected with a particular experiment in mind is challenging. So far we have explored whether recorded data can be used to determine whether automatically generated questions help children comprehend stories (Beck. Mostow, Cuneo et al. 2003 (in review)), to assess a student's reading proficiency based on the output of automated speech

recognition (Jia. Beck and Mostow 2002) to predict a student's help request behavior (Beck. Jia. Sison et al. 2003 (in review)), and to determine how a student's time allocation among different activities within the tutor affects his learning.

Sharon Carver. Director of the Carnegie Mellon Children's School. My research bridges the domains of cognitive development and educational psychology. In particular, I focus on using models of cognitive skills, such as program debugging or creating a research report, to design instruction and assessment that will facilitate skill acquisition and transfer in school contexts. In prior research. I collaborated with teachers in an urban school to design an innovative curriculum and learning environment for middle school. The curriculum was interdisciplinary, via extended projects and presentations. The learning environment consisted of essentially self-contained classes working collaboratively with adults (teachers, industry volunteers and researchers) who served as facilitators and coaches. We conducted longitudinal studies of the learning and transfer of research and communication skills using observation, interview, and protocol analysis techniques. As director of the Carnegie Mellon Children's School (http://www.psy.cmu.edu/childrensschool/). I am currently combining cognitive modeling. instructional design and focused assessment to explore how young children's developing problem solving skills can be enhanced to promote general transfer. The teachers and I are redesigning our three-year early childhood curriculum and assessment framework to focus more directly on the cognitive processes and rich knowledge base that provide an essential foundation for academic success after kindergarten. These studies of complex skill acquisition and transfer in realistic contexts help to refine cognitive theories of learning and transfer. In addition, these and other direct applications of cognitive psychology to education are particularly important in the face of increasing difficulty experienced by even the youngest children in America's schools.

Brian Junker, Professor of Statistics. I am interested in highly multivariate data for which we can discover an interesting and interpretable dependence structure. Data in education. psychology and the social sciences is often of this form: a student's right and wrong answers on a multiple-choice test, categories of solutions produced by a subject performing tasks in a cognitive psychology experiment, and responses to an interest inventory employed by a job counselor are all examples of this. A common tool for modeling the dependence structure in all of these examples is the latent variable model: each discrete response is treated as an indirect measure of some underlying entity, such as "proficiency", "attitude", "skill learned", etc., that we cannot measure directly. I have worked on problems in the statistical foundations of latent variable models for measurement, as well as applications of latent variable modeling in cognitive modeling, standardized testing, small-scale experiments in psychology and psychiatry, census enumeration, and large scale educational surveys such as the National Assessment of Educational Progress (NAEP). Large sample theory, probability inequalities, robust estimation. and hierarchical Bayes modeling techniques are all useful tools in these enterprises. (See Junker & Sijtsma, 2001: Patz. Junker, & Johnson, 2002: Johnson & Junker, 2003) Current research projects include developing computer-based assessment and tutoring facilities aimed at improving instruction relevant to student achievement accountability tests, statistical estimation and model selection relevant to cognitive modeling, the analysis of multilevel models in survey data, and the development of an assessment of instructional quality for K-12 teachers.

<u>David Klahr. Professor of Psychology (Program Director).</u> My research focuses on the development thinking processes that support scientific and mathematical thinking (Haverty, Koedinger, Klahr, & Alibali, 1999; Klahr & Simon, 1999). There are several related strands to this overall effort. Studies with pre-school children involve the determination of how young

children understand indeterminacy: that is, when they do and do not have sufficient evidence to reach an unambiguous conclusion (Klahr & Chen, 2003).

Another strand of my research has been the transformation of laboratory studies into the classroom, most specifically in studies of the effects of different instructional approaches and materials on middle school children's ability (Toth. Klahr. & Chen. 2000) to learn some of the fundamental inquiry procedures in experimental science. In these studies, Direct Instruction was compared to Discovery in the context of children's learning about how to design unconfounded experiments. While some children (about 25%) do manage to learn this important scientific procedure in Discovery conditions, many more (around 80%) achieve mastery of the procedure in the Direct Instruction condition. Further studies are underway to determine why some children are able to learn in Discovery conditions, while most are not. We are also trying to understand experimentally how students understand error and variability (Masnick & Klahr, 2003), and how they generate external notations for later use or whether physical or virtual materials are more effective, and whether different acquisition paths for procedural knowledge lead to different levels of far transfer. (Triona & Klahr, 2003, Klahr & Nigam, 2004).

Roberta Klatzky. Professor of Psychology My work lies at the interface between perceptual and cognitive processes. My two principal research areas are spatial cognition and haptic perception. My study of spatial cognition has been concerned with basic human abilities to learn about the layout of objects in space. Perceptual modalities -- vision, hearing, and touch -- provide direct spatial cues to the positions of objects around an individual. My work, however, has shown that people can learn about space not only from these intrinsically spatial modalities, but from descriptive language. Another theme in this work has been how the ability to learn reflects past perceptual experience. I have found that blind people as well as sighted can learn about space from language. Having heard a descriptive phrase, they can update self-position in space while walking without vision. My work on haptic perception, like that on spatial cognition, has dealt with the question of how learning is affected by the perceptual input channel. Haptics can be seen as a model for perceptually based learning in general, one that makes explicit the active, information-seeking nature of perception.

Ken. Koedinger, Associate Professor of Computer Science and Psychology. My background includes a BS in Mathematics, a MS in Computer Science, a PhD in Cognitive Psychology, and experience teaching in an urban high school. This multi-disciplinary preparation has been critical to my research goal of creating educational technologies that dramatically increase student achievement. Toward this goal, I create "cognitive models", computer simulations of student thinking and learning, that are used to guide the design of educational materials, practices and technologies. These "Cognitive Tutors" create rich problem solving environments for students to work in and provide just-in-time learning assistance much like a good human tutor does. I have developed Cognitive Tutors for mathematics and science and have tested them in the laboratory and the classroom. In a whole-year classroom study with our Algebra Cognitive Tutor. I have shown that students in our experimental classrooms outperformed students in control classes by 50-100% on targeted real world problem solving skills and by 10-25% on standardized tests. My research has contributed new principles and techniques for the design of educational software and has produced basic cognitive science research results on the nature of mathematical thinking and learning.

Marsha Lovett. Assistant Professor of Psychology. People are solving problems all the timein classrooms (e.g., What is the inverse of the function $y = 3x + \sin x$?) and in everyday life (e.g., How can I get dinner on the table by 6pm?). Generally speaking, when we solve problem after problem in a given area, we get better ("practice makes perfect"). But, unfortunately, this is not always the case (remember high school physics?!?). The Learning And Problem Solving Lab aims to study and model the internal, mental changes that occur when people solve problems, both to explain how people become proficient problem solvers and to identify common obstacles to learning. By developing a unified theory of how people learn during problem solving, we can both improve our understanding of how the mind works and aid the design of effective instruction. A major "applied cognitive psychology" project we are pursuing involves studying and improving students' learning in an introductory statistics course. We are developing and testing a cognitive tutor for statistics, called StatTutor, that helps students work through data-analysis problems. By studying how students learn in a real classroom setting and by testing instructional interventions in the laboratory and classroom, we can converge on the best practices while gaining a better understanding of learning in complex domains. (See: Meyer & Lovett, 2002: Lovett, 2001: Lovett & Greenhouse, 2000).

Brian Mac Whinney, Professor of Psychology Mac Whinney's work focuses on the acquisition of language both in family and classroom contexts. He is responsible for the construction of an online database of parent-child interactions called CHILDES (Child Language Data Exchange System) (MacWhinney, 2000) that has been used in over 1500 published research articles. More recently, he has extended the methods used for constructing CHILDES to create a wider system called TalkBank, designed to provide general tools for studying all forms of conversational interaction. One important part of the new TalkBank database is a growing collection of observational video with transcripts of interactions in classroom and tutorial contexts (MacWhinney, in press). Working with Roy Pea (Stanford), Chris Thorn (Wisconsin), Rich Lehrer (Vanderbilt), and Tim Koschmann (Southern Illinois), he has devised new transcript formats that promote a process called "collaborative commentary." One sample use of this method is to allow professors in graduate classes to work with their students to diagnose and understand classroom practices. Specific practices are coded in accord with an established coding scheme or set of standards. Disagreements between students in coding can be automatically detected and profiled and these mismatches can then become the subject of further analysis either in the college classroom or asynchronously over the web. By creating a video database that is linked directly to transcripts and codes and is also available over the web to collaborative commentary, classroom video data and child language data become useful for seven specific empirical methodologies, including: (a) Microanalytic studies. Microanalysis of videos relies on frame-by-frame analysis of linkages of conversation, gesture, proxemics, props. and prosodics. Koschmann and LeBaron (2002) provide illustrations of the application of this method to problem-based learning; (b) Microgenetic studies. Research programs that study cognitive development (Siegler & Crowley, 1991) use careful video analysis to track subtle changes in learner's strategies across days and weeks as a result of various types of teaching: (c) Planned comparisons. Within the TalkBank infrastructure, situations can be sampled across groups and conditions and compared in terms of analytic codings. For example, we can compare the gestures of deaf children of hearing parents with those of normal children in terms of a coding system delineating reference to the here and now (Morford & Goldin-Meadow, 1997). The coding system itself is then a focus of collaborative commentary. (d) Error analysis. We can. for example, distinguish cases of failed classroom communications by sampling across conditions and by microanalysis within conditions. (e) Longitudinal studies. In areas where controlled experimentation is not possible, longitudinal analysis is often equally powerful. For example, we can trace the process of mathematical development across the 12 years of Carolyn

Maher's video study of a cohort of learners in Baltimore. (f) Dynamic modeling. We can track individual differences in referential compression in dyadic interactions with computerized systems.

Jack Mostow, Research Professor, Robotics Institute. Project LISTEN (Literacy Innovation that Speech Technology ENables) is an inter-disciplinary research project at CMU to develop a novel tool to improve literacy -- an automated Reading Tutor that displays stories on a computer screen, and listens to children read aloud. To provide a pleasant, authentic experience in assisted reading, the Reading Tutor lets the child choose from a menu of high-interest stories from Weekly Reader and other sources -- including user-authored stories. The Reading Tutor adapts CMU's Sphinx-II speech recognizer to analyze the student's oral reading, and it intervenes when the reader makes mistakes, gets stuck, clicks for help, or is likely to encounter difficulty. The Reading Tutor responds with assistance modeled in part after expert reading teachers, but adapted to the capabilities and limitations of the technology. Our holy grail is "what helps?", that is, which tutorial interventions help which students, with which skills, under what conditions? Our tutorial data mining approach exploits the vast quantities of fine-grained, longitudinal student interactions captured by the Reading Tutor in thousands of hours of interaction with hundreds of children.

Richard Scheines. Professor of Philosophy. Automated Learning and Discovery, and Human-Computer Interaction. My research focuses on the connections between causal structure and data, especially the sort of data collected by social and behavioral scientists. We try to characterize what can and cannot be learned about causal structures from uncontrolled observations, from controlled experiments, randomized clinical trials, etc., under a variety of assumptions. My interests tend toward the problem of inferring the causal relations among "latent variables," i.e., variables that cannot be measured directly, like intelligence. Causal models of latent variables are used routinely in quantitative psychology, sociology, education research, and economics. Another large strand of my research focuses on developing and studying the educational effectiveness of online courses. Having developed a fully online course on Causal and Statistical Reasoning that has been used by almost 3,000 students in over 70 courses nationwide. I am interested in the features of the courseware that promote learning, and in using data collected on the student-course interaction to continuously improve student outcomes.

Robert Siegler, Professor of Psychology. My research focuses on the growth during childhood of problem solving and reasoning. Three areas of particular interest are strategy choices, long-term learning, and educational applications of cognitive-developmental theory. The research on strategy choices focuses on how children decide which strategy to use from among the many strategies they know. My research indicates that even four-year-olds choose among alternative approaches in surprisingly intelligent ways. The research on long-term learning examines how children discover new strategies. Small numbers of children are given prolonged experience in solving problems. Videotapes and verbal protocols obtained on each problem allow examination of the discovery, the circumstances leading up to it, and the subsequent generalization of the discovery to new problems. The emphasis is on individual differences in patterns of learning as well as commonalities in the learning of different children. For my most recent work in this area see Siegler & Stern. 1998: Crowley & Siegler. 1999: Chen & Siegler. 2000: Siegler. 2000; and Siegler & Svetina. 2002. The research has yielded a number of educational implications, particularly in the area of early mathematics. It is being used to develop tests to identify young children who are at risk for later mathematical difficulties. We are also developing programs for

preventing small, easy-to-remedy, early problems in mathematics from growing into large, intractable, later ones. (Rittle-Johnson, Siegler, & Alibali, 2001; Siegler, 2002; and Siegler, 2003.)

Paul Steif, Professor of Mechanical Engineering. My research focuses on learning and instruction in a core set of engineering subjects that have, thus far, received comparatively little scrutiny from the cognitive science community. We seek to identify fundamental concepts in these subjects, categorize errors that students make using these concepts, and identify antecedents of false conceptions in earlier science instruction. We also seek to determine whether methods of measuring conceptual knowledge and detecting misconceptions can be devised that are sufficiently rapid and efficient so as to practically affect the course of instruction for individual students. We are also active in revising curricula to reflect findings regarding conceptual challenges that students typically face. In addition, we seek to develop and test generalizable instructional approaches that facilitate the acquisition of conceptual knowledge and build powerful meta-cognitive strategies. Such instructional interventions are variously relevant to formal learning settings (classroom with possibly many students) and informal settings (small groups of students collaborating on out-of-class assignments).

IV. Resources

All IERP students will be provided with ample office space, individual computers, network access, central fileservers and mail systems, basic word-processing, communications, and computational software, backups, as well as specialized resources as necessary (e.g., digital video cameras, movie editing software, etc.). Predoctoral students in all participating departments have access to an extensive network of distributed workstations that are used to support simulation, presentation of stimuli and recording of subject responses, word processing, data analysis, administrative support, and electronic communications. These machines are all networked, and have access not only to Departmental machines, but also to many University printers and file systems located on campus, as well as all the resources available through the Internet. More specific resources available in individual departments are described in the Appendix.

Literature Cited

- Aist, G. (2001). Helping Children Learn Vocabulary during Computer-Assisted Oral Reading. Unpublished Ph.D. dissertation, Carnegie Mellon University, Pittsburgh, PA.
- Anderson & Lebiere, 1998
- Beck, J. E., J. Mostow, A. Cuneo and J. Bey (2003 (in review)). Can automated questioning help children's reading comprehension? *Proceedings of Eleventh International Conference on Artificial Intelligence in Education*.
- Beck, J. E., P. Jia and J. Mostow (2003 (in review)). Assessing Student Proficiency in a Reading Tutor that Listens. *Proceedings of Ninth International Conference on User Modeling*.
- Beck, J. E., P. Jia, J. Sison and J. Mostow (2003 (in review)). Predicting student help-request behavior in an intelligent tutor for reading. *Proceedings of Ninth International Conference on User Modeling*.
- Berliner, D.C. (2002). Educational Research: The Hardest Science of All. *Educational Researcher*, 31(8), 18-20.
- Carver, S. M. and Klahr D. (Eds.) (2001) *Cognition and Instruction: 25 years of progress*. Mahwah, NJ: Erlbaum
- Chen, Z. & Siegler, R. S. (2000). Across the great divide: Bridging the gap between understanding of toddlers' and older children's thinking. *Monographs of the Society for Research in Child Development*. 65, No. 2 (Whole No. 261).
- Corbett, A. T., Koedinger, K. R., & Hadley, W. H. (2001). Cognitive Tutors: From the research classroom to all classrooms. In Goodman, P. S. (Ed.) *Technology Enhanced Learning: Opportunities for Change*. (pp. 235-263). Mahwah, NJ: Lawrence Erlbaum Associates.
- Crowley, K., & Siegler, R. S. (1999). Explanation and generalization in young children's strategy learning. *Child Development*, 70, 304-316.
- Erosheva, E. (2004). Comparing Latent Structures of the Grade of Membership. Rasch. and Latent Class Models. Accepted, *Psychometrika*.
- Feuer, M.J., Towne, L. & Shavelson, R.J. (2002). Scientific Culture and Educational Research. *Educational Researcher*, 31(8), 4-14.
- Haverty, L., Koedinger, K. R., Klahr, D., & Alibali, M. (1999). Solving Induction Problems in Mathematics: Not-so-Trivial PURSUIT. *Cognitive Science*.
- Hoffer, T.B., S. Sederstrom, L. Selfa, V. Welch, M. Hess, S. Brown, S. Reyes, K. Webber, and I. Guzman-Barron. (2003). *Doctorate Recipients from United States Universities: Summary Report 2002.* Chicago: National Opinion Research Center.
- Jia, P., J. E. Beck and J. Mostow (2002). Can a Reading Tutor that Listens use Inter-word Latency to (better) Assess a Student's Reading Ability? *Proceedings of ITS 2002 Workshop on Creating Valid Diagnostic Assessments*.
- Johnson, M. S. and Junker, B. W. (2003). Using data augmentation and Markov chain Monte Carlo for the estimation of unfolding response models. *Journal of Educational and Behavioral Statistics*, 28, 195–230.

- Junker, B. W. and Gitelman, A. I. (2002). *Invited discussion of Bayesian Analysis of the New York School Choice Scholarship Program* by Barnard, Frangakis, Hill, and Rubin. Fifth Workshop on Bayesian Statistics in Science and Technology. Pittsburgh PA, September 24--25, 1999. Gatsonis, C., Kass, R. E., Carlin, B., Carriquiry, A., Gelman, A., Verdinelli, I., and West, M. (Eds.) (2002). *Case Studies in Bayesian Statistics V.* New York: Springer-Verlag.
- Junker, B. W. and Sijtsma, K. (2001). "Cognitive assessment models with few assumptions, and connections with nonparametric item response." *Applied Psychological Measurement*, 25.
- Klahr. D. & Nigam. M. (2004) The equivalence of learning paths in early science instruction: effects of direct instruction and discovery learning. *Psychological Science*
- Klahr, D., & Simon, H. (1999). Studies of scientific discovery: Complementary approaches and convergent findings. *Psychological Bulletin*, 125, 524-543.
- Koedinger, K. R., Anderson, J. R., Hadley, W. H., & Mark, M. A. (1997). Intelligent tutoring goes to school in the big city. *International Journal of Artificial Intelligence in Education*, 8, 30-43.
- Koschmann, T., & LeBaron, C. (2002). Learning articulation as interactional achievement: Studying the conversation of gesture. *Cognition and Instruction*, 20, 249-282.
- Labaree, D. F. (2003) The Peculiar Problems of Preparing Educational Researchers. *Educational Researcher*, 32, 4, 12-22.
- Lagemann, E. C. (2000). An Elusive Science: The Troubling History of Educational Research. Chicago: University of Chicago Press.
- Lockwood JR, Doran H, and McCaffrey DF (2003). "Using R for estimating longitudinal student achievement models." *The R Newsletter*, 3(3):17–23.
- Lovett, M. C. (2001). A Collaborative convergence on studying reasoning processes: A case study in statistics. In S. Carver, & D. Klahr (Eds.) *Cognition and instruction: Twenty-five years of progress* (pp. 347-384). Mahwah, NJ: Erlbaum.
- Lovett, M. C., & Greenhouse, J. B. (2000). Applying cognitive theory to statistics instruction. *The American Statistician*, 54, 196-206.
- MacWhinney, B. (2000) *The CHILDES Project: Tools for analyzing talk. Third edition.* Mahwah, NJ: Erlbaum.
- MacWhinney, B. (in press) TalkBank tools for analyzing classroom video. In Goldman. R., & Pea, R. (Eds.) *Video in the classroom*. Mahwah, NJ: Erlbaum.
- Mariano, L. T. and Junker, B. W. (2004). Covariates of the Rating Process in Hierarchical Models for Multiple Ratings of Test Items. Conditionally accepted. *Journal of Educational and Behavioral Statistics*.
- Masnick, A. M., & Klahr, D. (2003) Error Matters: An Initial Exploration of Elementary School Children's Understanding of Experimental Error. *Journal of Cognition & Development*. 4, 67-98
- McCaffrey DF, Lockwood JR, Koretz D and Hamilton L (2003). Evaluating Value-Added Models for Teacher Accountability. RAND MG-158-EDU, Santa Monica, CA.

- McCaffrey DF, Lockwood JR, Koretz D, Louis TA and Hamilton L (2004). "Models for value-added modeling of teacher effects (with discussion)," to appear, Journal of Educational and Behavioral Statistics.
- Meyer, O., & Lovett, M. C. (2002). Implementing a cognitive tutor in a statistical reasoning course: Getting the big picture. In Proceedings of the Sixth Annual International Conference on the Teaching of Statistics.
- Miller, D. W. (1999) The Black Hole of Education Research: Why do academics play such a minimal role in efforts to improve the schools. The Chronicle of Higher Education. 8/6/1999, 45, 58.
- Morford, J. P., & Goldin-Meadow, S. (1997). From here and now to there and then: The development of displaced reference in Homesign and English. Child Development, 68, 420-435.
- Mostow, J., & Aist, G. (1997, July). The Sounds of Silence: Towards Automated Evaluation of Student Learning in a Reading Tutor that Listens. *Proceedings of the* Fourteenth National Conference on Artificial Intelligence (AAAI-97), Providence, RI. 355-361.
- Mostow, J., Aist, G., Bey, J., Burkhead, P., Cuneo, A., Junker, B., Rossbach, S., Tobin, B., Valeri, J., & Wilson, S. (2002, June 27-30). Independent practice versus computerguided oral reading: Equal-time comparison of sustained silent reading to an automated reading tutor that listens. Ninth Annual Meeting of the Society for the Scientific Study of Reading, Chicago, Illinois.
- Mostow, J., Aist, G., Burkhead, P., Corbett, A., Cuneo, A., Eitelman, S., Huang, C., Junker, B., Sklar, M. B., & Tobin, B. (2003a). Evaluation of an automated Reading Tutor that listens: Comparison to human tutoring and classroom instruction. Journal of Educational Computing Research, 29(1), 61-117.
- Mostow, J., Aist, G., Huang, C., Junker, B., Kennedy, R., Lan, H., Latimer, D., O'Connor, R., Tassone, R., Tobin, B., & Wierman, A. (2004, in press). 4-Month Evaluation of a Learner-controlled Reading Tutor that Listens. In V. M. Holland & F. N. Fisher (Eds.). Speech Technology for Language Learning, Lisse, The Netherlands: Swets & Zeitlinger Publishers.
- Mostow, J., Beck, J. E., & Valeri, J. (2003c, June 22). Can Automated Emotional Scaffolding Affect Student Persistence? A Baseline Experiment. Proceedings of the Workshop on "Assessing and Adapting to User Attitudes and Affect: Why, When and How?" at the 9th International Conference on User Modeling (UM'03), Johnstown, PA, 61-64.
- Mostow, J., Beck, J., Bey, J., Cuneo, A., Sison, J., & Tobin, B. (2003b, June 12-15). An Embedded Experiment to Evaluate the Effectiveness of Vocabulary Previews in an Automated Reading Tutor. Tenth Annual Meeting of the Society for Scientific Studies of Reading. Boulder. CO.
- Mostow, J., Beck, J., Bev, J., Cuneo, A., Sison, J., Tobin, B., & Valeri, J. (to appear). Using automated questions to assess reading comprehension, vocabulary, and effects of tutorial interventions. Technology. Instruction. Cognition and Learning, 2.

- Mostow, J., Roth, S. F., Hauptmann, A. G., & Kane, M. (1994, August). A prototype reading coach that listens [AAAI-94 Outstanding Paper Award]. *Proceedings of the Twelfth National Conference on Artificial Intelligence*, Seattle, WA, 785-792.
- National Research Council (2001). Knowing what students know: The Science and Design of Educational Assessment. Committee on the Foundations of Assessment. Pelligrino. J., Chudowsky, N., and Glaser, R., editors. Board on Testing and Assessment. Center for Education. Division of Behavioral and Social Sciences and Education. Washington. DC: National Academy Press.
- National Research Council (2002). *Scientific research in education*. Committee on Scientific Principles for Education Research. R.J. Shavelson and L. Towne (Eds.). Center for Education. Division of Behavioral and Social Sciences and Education. Washington. DC: National Academy Press.
- National Research Council (2004). *Implementing Randomized Field Trials in Education: Report of a Workshop.* Committee on Research in Education. L. Towne and M. Hilton. Eds. Center for Education. Division of Behavioral and Social Sciences and Education. Washington, DC: The National Academies Press.
- Pane, J.F. (2002). A Programming System for Children that is Designed for Usability. Ph.D. Thesis, Carnegie Mellon University, Computer Science Department, CMU-CS-02-127, Pittsburgh, PA.
- Patz. R. J. and Junker. B. W. (1999). Applications and extensions of MCMC in IRT: Multiple item types, missing data, and rated responses. *Journal of Educational and Behavioral Statistics*, 24, 342--366.
- Patz. R. J., Junker, B. W., Johnson, M. S. and Mariano, L. T. (2002). The hierarchical rater model for rated test items and its application to large-scale educational assessment data. *Journal of Educational and Behavioral Statistics*. 27, 341–384.
- Rittle-Johnson, B., Siegler, R. S., & Alibali, M. W. (2001). Developing conceptual understanding and procedural skill in mathematics: An iterative process. *Journal of Educational Psychology*, *93*, 346-362.
- Scheines, R., Leinhardt, G., Smith, J., and Cho, K. Teaching and Learning with Online Courses." (2003). *Technical Report No. CMU_PHIL-135*, Dept. of Philosophy, Carnegie Mellon University, Pittsburgh, PA, 15213. (Under review at Journal of Educational Technology)
- Siegler, R. S. & Stern, E. (1998). Conscious and unconscious strategy discoveries: A microgenetic analysis. *Journal of Experimental Psychology: General*. 12⁻⁷, 377-397.
- Siegler, R. S. (2000). The rebirth of children's learning. *Child Development*, 71, 26-35. Reprinted in C. Desforges & R. Fox (Eds.) (2002). *Teaching and learning: The essential readings* (pp. 63-83). Malden, MA: Blackwell.
- Siegler, R. S. (2002). Microgenetic studies of self-explanations. In N. Granott & J. Parziale (Eds.). *Microdevelopment: Transition processes in development and learning* (pp. 31-58). New York: Cambridge University.
- Siegler, R. S. (2003). Implications of cognitive science research for mathematics education. In Kilpatrick, J., Martin, W. G., & Schifter, D. E. (Eds.), *A research companion to principles and standards for school mathematics* (pp. 289-303). Reston, VA: National Council of Teachers of Mathmatics.

- Siegler, R. S., & Svetina, M. (2002). A microgenetic/cross-sectional study of matrix completion: Comparing short-term and long-term change. *Child Development*. 73, 793-809.
- Siegler, R., & Crowley, K. (1991). The microgenetic method: A direct means for studying cognitive development. American Psychologist, 46, 606-620.
- Spirtes, P., Glymour, C., and Scheines, R. (2000) Causation. Prediction, and Search. 2nd Edition, MIT Press.
- Stokes, D. E. (1997) *Pasteur's Quadrant: Basic Science and Technological Innovation*. Brookings Institution Press.
- Toth, E., Klahr, D., & Chen, Z. (2000). Bridging research and practice: A cognitively-based classroom intervention for teaching experimentation skills to elementary school children. *Cognition and Instruction*. *18*, 423-459.
- Triona and Klahr (notation chapter. in press)
- Triona. L., & Klahr, D. (2003). Point and click or grab and heft: Comparing the influence of physical and virtual instructional materials on elementary school students' ability to design experiments. *Cognition and Instruction*, 21, 149-173.
- Viadero, D. (2004). The skills gap. Education Week, 23 (16), 30, 31, 33
- Weiss, A.R., Lutkus, A.D., Hildebrant, B.S., and Johnson, M.S. (2002). The Nation's Report Card: Geography 2001, NCES 2002-484, U.S. Department of Education. Office of Educational Research and Improvement. National Center for Education Statistics. Washington, DC.

Curriculum Vita of Key Personnel

Budget Narrative

Student stipend, tuition, travel. The budget uses the suggested amounts for trainee stipends, tuition, and travel costs, applied to the estimated number of trainees in the program depicted in this table. Year 1 estimates are based on students currently in the graduate programs in different departments who are already engaged in educational research. Here we expand the table shown in section I.6.2, to include more detail about trainee flow through the program. (Estimates of departmental allocations are not included in this analysis.)

	2004-05	2005-06	2006-07	•	2007-08	200	8-09	2009-2010	2010-2011
current 2nd		4	4	4				ļ	
current 3rd		3	3						
enter 2005			8	8		8	8	8	
enter 2006	1			8		8	8	8	
enter 2007						4	4	4	
TOTAL IN PROGRAM		7	15	20	2	0	20	20	12

Each row in the table corresponds to an entering cohort. In the first year of the program, we estimate that 4 students current in their second year of graduate training, and 3 in their third year (distributed across the participating departments) would qualify for support by the training grant. They would remain in the program for three more and two more years, respectively. We estimate that in the Fall of 2005. 8 new students would enter. 8 more in 2006, and 4 more in 2007. Note that the expected training period for all students entering in 2006 or later, would extend beyond the grant period. While we would hope that we would be able to renew support for the training grant for another extended period, this is not guaranteed in any way. Therefore, we have "backloaded" the budget in year 5 to provide funding for at least half of these "legacy" students. with the expectation that we will be able to find other sources for supporting their final years of their doctoral training. Thus, the final budget year includes the "carryforward" estimate, which is then used to pro-rate all student based costs: stipend, tuition, travel, etc. The table below summarizes these estimates:

		2004-05	2005-06	2006-07	2007-08	2008-09
	Psych		4	7	9	9
	Śtat		1	3	4	4
	HCII		2	3	4	4
; - -	Other		0	2	3	3
Carryforward						1
	Total		7	15	20 2	20 3

Project director. Will devote one equivalent of one AY month and one summer month (distributed over the calendar year) to program development and management.

Program Coordinator. This is a 1/2 time staff appointment for a person who will assist with all aspects of interdepartmental coordination, record keeping, preparation of recruiting and outreach materials, scheduling of core courses, and other clerical and administrative aspects of the IERP. The Staff Assistant will work closely with the Graduate Training Directors in each of the affiliated departments, to help coordinate their standard graduate training with the special aspects of the IERP.

New Faculty. Starting in year 2 (2005-2006 AY), we have budgeted for 50% of the salary of a new faculty member whose primary research agenda is associated with the scientific focus of the IERP.

Colloquium costs: Based on estimate of 4 outside speakers per year for a 1.5 day visit to give a colloquium talk, an informal talk, and to meet individually with graduate students in the program.

Travel costs. Based on estimated per-student cost for one IES meeting and one professional conference per year, plus extra costs for proactive minority recruiting and site visits.

Appendix A

A.1 Resources available to IERP trainees

A.1.1 Psychology Department Resources.

Within the Psychology Department alone, there is a computing support staff that includes a Manager of Computing Operations, an Engineer, and 2 additional full-time operational/technical staff members. In addition, several of the larger individual faculty laboratories have their own programmers and computing operations staff. Other participating departments (Statistics, Human Computer Interaction, etc.) have equivalent physical resources and support personnel. A number of laboratories include several special purpose tools: these include extensive video recording facilities, an automated eye-tracking system linked to computer-driven displays, and a tutoring laboratory.

For researchers interested in early childhood education, the Carnegie Mellon Children's School (a preschool with roughly 100 3-, 4-, and 5-year-olds) provides access for a variety of studies. In addition, CMU has a long history of school based research in a very wide variety of public, private, and parochial schools in the Pittsburgh region. In any given year CMU's school-based studies involve scores of classrooms and several hundred students. At the college level, there is a long history of interdisciplinary collaboration among CMU faculty on creating experimental instructional materials and on various ways of seamlessly integrating assessments of educational experiments into ongoing classes.

A.1.2 Statistics Department Resources

The Department of Statistics operates its own computer facilities which provide students with experience using over eighty advanced graphics workstations. The workstations are interconnected by a departmental Fast Ethernet which, in turn, is connected to University and worldwide networks. Twenty workstations are located in two department-owned computer rooms: these computers are designated primarily for graduate student use. In addition, there are several Windows-based PC's, and laser printers. The Department also has a graphics laboratory with equipment for producing computer-animated video tapes and computer-generated color graphics. In 2000, the Department of Statistics at Carnegie Mellon, with partial support from a National Science Foundation SCREMS grant, purchased a 128 CPU mini-supercomputer. This computer, combined with the department's existing 16 processor computer, provides unprecedented computing capacity. The new machine has a total memory of 34 gigabytes, a total disk capacity of more than 1 terabyte, and a computational throughput of approximately 1 teraflop.

All students have unlimited access to all of the computing equipment. Students and faculty use the facilities in a variety of creative ways. Some work on very large datasets such as data collected from complex manufacturing processes or large-scale surveys such as the U.S. National Crime Survey and the U.S. Census. Others run computationally intensive simulations of stochastic systems, study numerical methods for implementing Bayesian inference, or experiment with novel ways of visualizing data. The Department and University support a wide range of standard and experimental statistical software. The Department believes that computation is an essential tool for applied statistics and that the theory of computational methods is an important area of research. For these reasons, the Department provides an introduction to the computing environment to all new students. Furthermore, the hardware and software are upgraded on a regular basis to ensure that the facilities remain current.

A.2 Summary statistics on recent years for the Psychology PhD program.

Total # applicants # male, # female	current year- 2003-2004 197 82m, 115f 34 minority, 42	2002-2003 181 68 m, 113 f 40 minority, 44	2001-2002 153 unknown	2000-2001 177 unknown
minority Total # accepted # male, # female minority	unanswered, 121 cauc 14* 4m, 10f 2	unanswered, 97 cauc 18* 7 m, 11 f 3	unknown 11 5 m, 6 f unknown	unknown 13 6 m, 7 f unknown
Total # enrolled # male, # female minority	11 3m, 8f 1 5 (by end of	9 3 m, 6 f 3 8 (by end of	4 1m, 3 f 1	8 4 m, 4 f 1
Total # PhDs awarded # male, # female minority	August '04) 4m, 1f	August '03) 6m, 2 f 3	2 2 m 0	4 3 m, 1 f 0
Total # grad students # male, # female minority	34 15m, 19f 5	30 16m, 14 f 5	26 15 m, 11 f 4	22 14 m, 8 f 3

TABLE A1.

Recent PhD. Dissertations in Statistics and Computer Science with Relevance to Educational Research

2002

Grade of Membership and Latent Structure Models with Application to Disability Survey Data. Elena A. Erosheva:

Bayesian Semiparametric Inference for Statistical Models Using Mixtures, Roberto Carta;. Information Accumulation, Model Selection and Rater Behavior in Constructed Response Student Assessments, Louis T. Mariano:

Helping Children Learn Vocabulary during Computer-Assisted Oral Reading. (A Distinguished Finalist for the International Reading Association's Outstanding Dissertation Award). Gregory Aist

A Programming System for Children that is Designed for Usability. John Pane

2001

Statistical Models for Classification and Discrimination, with Application to Classifying Web Documents, Stella M. Salvatierra:

Statistical Tools for Disclosure Limitation in Multi-Way Contingency Tables, Adrian Dobra: Analyzing Longitudinal Data with Mixture Models: A Trajectory Approach, Bob Jones:

2000

The Juvenile Homicide Epidemic: Spatio-Temporal Dynamics of Homicide in American Cities. Dan Cork:

Treatment Integrity Concerns in Comparative Education Studies. Alix I. Gitleman:

Model Sensitivity in Research on Welfare and Fertility, Terra McKinnish:

1998

An Approach for Selection of Nonparametric Regression Methods, Ashish Sanil:

1997

Bayesian Design of Experiments for the Linear Model. Isabella Verdinelli:

Nonparametric Bayesian Methods for Evaluating Fit in Hierarchical Models, Kert Viele:

1996

Markov Chain Monte Carlo Methods for Item Response Theory Models With Applications for NAEP.

The Schwarz Criterion For Mixed Effects Models. Donna Kay Pauler:.

1995

Probabilistic Analysis of Association Reversal Phenomena. Petros I. Hadjicostas:.

On Order Selections of Continuous Autoregressive Processes, Tao Jiang.

State Space Modeling of Long-Memory Processes, Wilfredo Palma:

1994

Interactive Navigation for Local Viewing in Multivariate Datasets. Shingo Oue:.

Issues in Combining Information: Hierarchical Models, Selection Models, and Unobserved Data, Nancy Paul Silliman:

1993

A Bayesian Approach to Measuring the Size of HIV/AIDS Epidemic, Yu-Chiao Chang: Experimental Studies by Distinct Designer and Estimators. Madhumita Lodh:.

Local Sensitivity of Posterior Expectations. Paul Gustafson:

1992

Stochastic Control of Sequential Manufacturing Processes, Suresh K. Vaidyanathan:

1991

Two Classes of Non-Linear Time Series Models. Rong Chen: Capture-Recapture Census with Uncertain Matching. Ye Ding:

Optimal Scheduling of Inspections with an Application to Medical Screening Tests. Giovanni Parmigiani:

Appendix 4

TABLE A2. Recent Psychology and Computer Science PhDs with positions in educational or applied research

NAME	ADVISOR	YEARS IN PROGRAM	CURRENT AFFILIATION
IRVIN KATZ	ANDERSON	1984-1988	SCIENTIST. EDUCATIONAL TESTING SERVICE
MARY HEGARTY	JUST	1984-1988	FACULTY. UNIV OF CA @ SANTA BARBARA
CAROLANNE FISHER	SIMON	1984-1991	CONSULTANT. QUINTUS DESIGN
KEN KOEDINGER	ANDERSON	1986-1990	FACULTY. HUMAN- COMPUTER INTERACTION INSTITUTE. CMU
STEVEN RITTER	MACWHINNEY	1988-1992	COGNITIVE SCIENTIST. CARNEGIE LEARNING CENTER
KATHLEEN CHRISMAN	CLARK	1988-1993	ADMINISTRATOR, CARLOW COLLEGE
DAVID PENNER	KLAHR	1989-1993	SCHOOL OF EDUCATION. UNIVERSITY OF WISCONSIN)
MARSHA LOVETT	ANDERSON	1989-1994	FACULTY, CMU PSYCHOLOGY DEPT.
KEVIN CROWLEY	SIEGLER	1989-1994	FACULTY, LRDC. UNIVERSITY OF PITTSBURGH
TAKESHI OKADA	SIMON	1989-1994	FACULTY, NAGOYA UNIVERSITY
PRITI SHAH	CARPENTER	1990-1995	FACULTY, JOINT APPOINTMENT/DEPT, OF PSYCHOLOGY & EDUCATION, UNIVERSITY OF MICHIGAN
CHRISTIAN SCHUNN	KLAHR	1990-1995	FACULTY, LRDC, UNIVERSITY OF PITTSBURGH
TERRI HUSTON	J. COHEN	1991-1996	EBERLY CENTER FOR TEACHING EXCELLENCE. CMU
STEVE BLESSING	ANDERSON	1992-1996	COGNITIVE SCIENTIST. CARENGIE LEARNING CENTER
ADISACK NHOUYVANISVO NG	KOEDINGER	1994-1999	PSYCHOMETRICIAN. PEARSON VUE. MINNESOTA
LISA HAVERTY	KOEDINGER AND ANDERSON	1994-1999	COGNITIVE SCIENTIST. CARNEGIE LEARNING

BETHANY RITTLE-JOHNSON	SIEGLER	1994-1999	ASSISTANT PROF., PEABODY COLLEGE OF EDUCATION.
KITTLE-JOHNSON			VANDERBILT
DOUGLAS	SIEGLER	1994-1999	SENIOR RESEARCH
THOMPSON			SCIENTIST. MARYLAND
			MEDICAL RESEARCH
			INSTITUTE, BALTIMORE, MD
NEIL HEFFERNAN	KOEDINGER	1996 - 2001	ASSISTANT PROFESSOR OF
			COMPUTER SCIENCE
			WORCESTER POLYTECHNIC
			INSITUTE
MICHAEL (MIKE)	ANDERSON	1996-2000	RESEARCH PSYCHOLOGIST.
MATESSA			NASA AMES RESEARCH
			CENTER, CA
KEN KWOK	MCCLELLAND	1998-2003	COGNTIVE SCIENTIST.
			SINGAPORE NAVY
GLENN	ANDERSON	1999-2003	POST-DOC, AIR FORCE.
GUNZELMANN			PHOENIX
JUNLEI LI	HAYES &	1999-2004	POST-DOC. PSYCHOLOGY.
· · · · · · · · · · · · · · · · · · ·	KLAHR	1	CARNEGIE MELLON
			UNIVERSITY
LARA TRIONA	KLAHR	1999-2004	POST-DOC, UC SANTA CRUZ
	I I		OR RESEARCHER, SAN
			FRANCISCO
	:		EXPLORATORIUM (not decided
	į		yet)

TABLE A3
Recent Statistics PhDs with positions in educational or applied research

Name	Advisor	Years in Program	Affiliation
Amelia Haviland	Fienberg	1998-2002	RAND, Pittsburgh
Louis T. Mariano	Junker	1997-2002	RAND. Washington DC
Elena Erosheva	Fienberg	1997-2002	Faculty, Univ of Washington
Matt Johnson	Junker	1997-2001	Faculty, Baruch College CUNY
J.R. Lockwood	Schervish	1998-2001	RAND, Pittsburgh
Alix Gitelman	Junker	1994-2000	Faculty, Oregon State U
Richard Patz	Junker	1991-1996	Consultant and Adjunct Faculty, Stanford.
Tao Jiang	Chan	1991-1995	Amer. Institutes for Research, Wash. DC

	Year 01	Year 02
	09/01/04 -	09/01/05 -
	08/31/05	08/31/06
Personnel:		
 * Graduate Student, Stipend 	210,000	450,000
 * Graduate Student, Tuition 	73,500	157,500
(Tuition, Health Insurance, and Normal Fe		
Total Graduate Student Support	283,500	607,500
Program Coordinator, 50% CY	15,450	15,914
Project Director, 1 Su and 1 AY	33,687	34,697
New Faculty Recruitment	<u>-</u>	33,475
Total Salaries	332,637	691,586
Fringe Benefits @ 26.30%	12,923	22,115
(excludes graduate student support)	345,560	713,700
Other Expenses:		
Colloquia (4 speakers each year)		
Per item cost/average:		
Travel (average \$700)	2,800	2,884
Hotel (cost \$280)	1,120	1.154
Reception (Cost \$100)	400	412.
Dinner (Department Policy \$240)	960	989
Lunch (Approx. cost \$60)	240	247
Total	5,520	5,686
Research Expenses for Fellows	25,000	25,000
Total Other Expenses:	30,520	30,686
Travel:		
Program Director - 2 day kick-off trip	1,400	_
PD and Fellows - 2 day trip to DC @ 1K each	11,200	22.400
Fellows - Professional conferences @ 1K each	10,500	22,500
Outreach Recruiting for Minorities	5.000	5.150
Total Travel	28.100	50.050
Total Direct Costs	404.180	794,436
F&A (Indirect Costs @ 8% MTDC) ***	9,654	14,955
Total Sponsor Costs	413.834	809,391
	*	

^{*} Grad student numbers as shown below - stipend @ 30K each

^{***} F&A: MTDC = TDC Less Stipends, Tuition and Related Fees, and Capital Expenditures o

	2004-05	2005-06
Psych	4	. 7
Stat	1	3
HCII	2	3
Other	0	2
Carryforward		

Tota	nl 7	15
	2004-05	2005-06
current 2nd	4	4
current 3rd	3	3
enter 2005		8
enter 2006		
enter 2007		
TOTAL IN PROGRAM	VI7	15

Year 03	Year 04	Year 05	Total
09/01/06 -	09/01/07 -	09/01/08 -	09/01/04 -
08/31/07	08/31/08	08/31/09	08/31/09
600,000	600,000	1.050,000	2,910.000
210,000	210,000	367,500	1,018,500
			·
810,000	810.000	1,417,500	3,928,500
16,391	16,883	17,389	82,026
35,738	36,810	37,915	178,847
34,479	35,514	36.579	140,047
896,608	899,207	1,509,383	4,329,420
22,778	23.461	24.165	105,442
919,386	922,668	1,533,548	4,434,863
			-
2,971	3,060	3,151	14,866
1,188	1,224	1.261	5,946
424	437	450	2.124
1,018	1,049	1,080	5,097
255	262	270	1.274
5.856	6,032	6,213	29.306
25.000	25,000	25.000	125.000
30,856	31.032	31,213	154,306
-	-		1,400
29,400	29.400	50,400	142,800
30.000	30.000	52,500	145.500
5.305	5.464	5.628	26.546
64.705	64,864	108.528	316.246
			3.3.2.10
1.014,947	1.018,563	1,673,288	4.905.415
16,396	16.685	20,463	78.153
1,031,343	1.035.249	1,693,751	4,983,568
		,===,: -	,,,,,,,,,,

of 5K or more

2006-07	2007-08	2008-09
9	9	9
4	4	4
4	4	4
3	3	3
		15

20 20	35
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2006-07 4	2007-08	2008-09	2009-2010	2010-2011
8	8	8	8	
8	8	8	8	8
	4	4	4	4
20	20	20	20	12